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Original Article

Brain–Computer Interface Games for Cognitive Assessment: A Scoping Review

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ABSTRACT: ***Background:*** Traditional cognitive assessments rely on verbal or motor responses, posing challenges for individuals with communication or mobility impairments. Brain–computer interface (BCI) games could enable cognitive assessments without motor or verbal demands. ***Objective:*** This scoping review synthesizes the current literature on BCI games for cognitive assessment, identifying trends, gaps and future research directions, to inform the development of more accessible electroencephalogram (EEG)-based tools. ***Methods:*** Seven electronic databases were systematically searched using Arksey and O'Malley's framework and Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for Scoping Reviews guidelines. Studies were reviewed based on game types, BCI paradigms, electrode placement, brainwave frequencies and cognitive skills assessed. Study design, population characteristics and comparisons to standardized assessments were extracted. ***Results:*** Of the 4735 screened studies, 33 met the inclusion criteria, totaling 694 participants. Most studies (61%) examined adults, 33% focused on children and 6% on older adults. Neurotypical individuals comprised 76%, with 18% having attention deficit hyperactivity disorder. Attention was the most studied cognitive skill (88%), followed by memory (27%), inhibition (18%) and spatial perception (12%). The most used BCI devices were MindWave (42%) and Emotiv EPOC+ (21%), which analyzed β and θ brainwaves. Only 27% investigated the relationship between BCI games and cognitive standardized assessments, with most showing moderate-to-strong correlations. ***Conclusion:*** BCI games show promise as adapted cognitive assessment tools but require further validation. Expanding research beyond attention to include diverse populations will enhance inclusivity. The predominance of attention-focused tasks and consumer-grade EEG devices highlights the need for rigorous, population-specific validation frameworks to advance BCI games as clinically credible assessment tools.

RÉSUMÉ : Jeux reposant sur une interface cerveau-machine en vue d'une évaluation cognitive : une revue exploratoire. ***Contexte :*** Les évaluations cognitives traditionnelles sont axées sur des réponses verbales ou motrices, ce qui pose des difficultés aux personnes souffrant de troubles de la communication ou de la mobilité. À cet égard, les jeux reposant sur une interface cerveau-machine (ICM) pourraient permettre des évaluations cognitives sans exigences de nature motrice ou verbale. ***Objectif :*** Cette revue exploratoire entend synthétiser la littérature actuelle portant sur les jeux reposant sur une ICM qui sont destinés à l'évaluation cognitive. Elle entend aussi identifier les tendances, les lacunes et les orientations futures de la recherche afin d'éclairer le développement d'appareils d'électroencéphalographie (EEG) plus accessibles. ***Méthodes :*** Au total, 7 bases de données électroniques ont fait l'objet d'une recherche systématique à l'aide du cadre méthodologique d'Arksey et O'Malley et des lignes directrices PRISMA-ScR. Les études ont été examinées en fonction des types de jeux, des paradigmes d'ICM, du placement des électrodes, des fréquences des ondes cérébrales et des compétences cognitives évaluées. La conception de l'étude, les caractéristiques de la population et les comparaisons avec des évaluations standardisées ont été ensuite extraites. ***Résultats :*** Sur les 4 735 études examinées, 33 répondaient à nos critères d'inclusion, et ce, pour un total de 694 participants. La plupart des études (61 %) portaient sur des adultes, 33 % sur des enfants et 6 % sur des personnes âgées. Les individus neurotypiques représentaient 76 % des participants, tandis que 18 % souffraient de trouble de déficit de l'attention avec ou sans hyperactivité (TDAH). L'attention était la capacité cognitive la plus étudiée (88 %), suivie de la mémoire (27 %), de l'inhibition (18 %) et de la perception spatiale (12 %). Les dispositifs d'ICM les plus utilisés étaient MindWave (42 %) et Emotiv EPOC+ (21 %), lesquels permettaient d'analyser les ondes cérébrales β et θ. Enfin, seules 27 % des études ont examiné la relation entre les jeux reposant sur une ICM et les évaluations cognitives standardisées, la plupart montrant des corrélations modérées à fortes. ***Conclusion :*** Les jeux reposant sur une ICM semblent prometteurs en tant qu'outils d'évaluation cognitive adaptés, mais nécessitent toutefois une validation plus approfondie. Élargir la recherche au-delà de l'attention pour inclure des populations diverses renforcera l'inclusivité. De plus, la prédominance de tâches axées sur l'attention et d'appareils d'EEG grand public souligne la nécessité de

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cadres de validation rigoureux et spécifiques à chaque population pour faire progresser les jeux reposant sur une ICM en tant qu'outils d'évaluation fiables sur le plan clinique.

Keywords: attention deficit; cognition; EEG; memory; neuro-rehabilitation

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Highlights

- BCI games enable engaging, direct cognitive assessment without motor or verbal demands.
- Most studies focus on healthy adults and attention, with limited research on diverse populations and broader cognitive domains.
- Validated against standardized tests, BCI games show potential as inclusive and accessible assessment tools.

Introduction

Cognition encompasses the mental processes involved in acquiring knowledge, processing information and engaging meaningfully with the world.[1] Consequently, a comprehensive understanding of cognitive abilities is essential, as changes in these areas can be early indicators of various neurological conditions.[2] By accurately assessing these cognitive processes, clinicians and researchers can better understand brain function, facilitating precise diagnoses and enabling interventions tailored to an individual's unique cognitive profile.[3] Traditional assessment tools, such as the Alzheimer's Disease Assessment Scale–Cognitive Subscale and the Wechsler Intelligence Scale for Children (WISC-V), have been widely used to evaluate cognitive functions across different age groups.[4,5] However, these assessments often depend on verbal or motor responses, such as naming objects, recalling and repeating words, using a pencil or manipulating objects, which can present challenges for individuals with limited communication or mobility.[6] As a result, these tools may not fully capture the individual's cognitive abilities, potentially underestimating their cognitive capacity.[7] This underscores the need for alternative or adaptive assessment methods that reduce motor and verbal demands and assess cognition independent of physical or communicative limitations.

Technology integration into cognitive science has transformed cognitive assessment, addressing many limitations inherent in traditional methods.[8,9] Among the most promising developments are brain–computer interfaces (BCIs), which record and interpret neural signals directly, bypassing the need for motor or verbal responses.[10,11] Of particular interest are BCI-controlled games, which go beyond standard BCI paradigms by embedding cognitive tasks within interactive, gamified environments.[12,13] This design approach enhances user engagement and ecological validity; assessments feel less clinical and more naturalistic, which is especially valuable for children and individuals with impairments.[14,15] The combination of real-time neural recording and motivating gameplay offers a richer, more authentic window into cognitive function than traditional tools can provide.[16] This is particularly relevant for individuals with conditions such as cerebral palsy (CP) or amyotrophic lateral sclerosis, who may be physically unable to perform the motor-based responses that traditional assessments require and can confound results and lead to underestimation of true cognitive ability.[17] For these populations, BCI games offer a clinically meaningful alternative, one that captures neural correlates of cognition, without placing undue burden on motor or communication abilities.

Previous studies have demonstrated the growing potential of BCI technology for cognitive assessment. A review analyzed the application of BCIs in neurotypical populations, highlighting the diverse methods for assessing cognitive skills, including auditory and visual attention tasks with a focus on user-appropriate control strategies to enhance BCI performance and usability.[18] Another systematic review examined the use of BCIs in neurotypical populations and individuals with neurological disorders, identifying factors influencing the usability and efficacy of these systems, with particular emphasis on why standard BCI training protocols need to be revised to improve engagement and data quality.[19] While both contributions advanced our understanding of BCI usability and training, neither focused specifically on game-based applications for cognitive assessment, nor did they evaluate how BCI-based tools compare against standardized neuropsychological measures. This scoping review addresses that gap by focusing specifically on BCI games as cognitive assessment instruments, evaluating their design, the cognitive domains they target and their comparability to validated neuropsychological measures across diverse populations.

Despite the growing interest in BCI technology for cognitive assessment, several critical knowledge gaps remain. Current research has primarily focused on proof-of-concept studies or small-scale trials, often emphasizing the technical feasibility of BCI systems rather than their broader applicability or integration.[20,21] While many studies have demonstrated the potential of BCI games to engage users and assess specific cognitive skills, there is limited research on their comparative validity and reliability against standardized cognitive assessment tools.[22] This lack of benchmarking limits the generalizability and clinical adoption of BCI-based methods. Furthermore, existing studies often concentrate on healthy individuals, neglecting other groups, such as those with motor or cognitive impairments.[23] To the best of our knowledge, there is insufficient exploration of BCI games for cognitive assessment in populations with developmental disorders or age-related cognitive decline, leaving a gap in understanding how BCI games can be tailored to these populations' unique cognitive and physiological needs.[24] Although several reviews have examined BCIs more broadly, few have focused specifically on game-based applications for cognitive assessment. Existing reviews have primarily emphasized technical feasibility or rehabilitation applications, with limited attention to validating BCI games against standardized cognitive assessments or exploring their use across diverse populations.[24–26] This review aims to map and analyze existing BCI games for cognitive assessment, examining trends across populations, cognitive domains and device technologies to identify gaps and inform future research directions. Specifically, we map, classify and critically evaluate BCI games used for cognitive assessment across populations, cognitive domains, devices and paradigms and their comparability with standardized assessment tools, through the following questions:

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1. What BCI games are currently used for cognitive assessment, and in which populations?
2. Which cognitive or perceptual skills are measured by these BCI games, and how were they measured?
3. How do these BCI games for cognitive assessment compare to standardized and traditional methods?
4. What BCI technologies are used to assess cognition, what electrode placement is used and what brain waves are explored?

Methods

Design

We followed Arksey and O'Malley's scoping review approach and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews guidelines.[27,28] Various strategies during the review process minimized bias. To address source bias, we searched for relevant papers across multiple databases.[29] To ensure high conceptual and methodological rigor, we included only those published in peer-reviewed journals and conference papers.[30] During the paper selection process, two raters independently screened papers, with a third rater resolving any disagreements to mitigate potential rater bias in applying inclusion criteria.

Inclusion and exclusion criteria

Papers that included a BCI game to assess cognitive skills were considered. To ensure a comprehensive understanding of the current state of BCI research, this scoping review encompasses studies from all age groups, as research in BCI remains limited. Papers published in the last 10 years, in English, available in full text and appearing in peer-reviewed journals or conference proceedings were included. The 10-year timeframe was selected to capture the period of rapid growth in consumer-grade electroencephalogram (EEG) devices and BCI gaming applications, during which the majority of relevant research in this field has emerged. Master's or doctoral thesis dissertations, one-page abstracts, gray literature and review papers were excluded. Full details regarding the inclusion and exclusion criteria are presented in Appendix A.

Search strategy

Our team developed key concepts, including BCI games and cognitive assessment, to guide the search. Using these concepts, keywords were combined with Boolean operators, and a health sciences librarian reviewed and approved our final search strategy. Appendix A provides detailed information regarding the search strategy.

Data sources

A systematic database search was conducted using seven electronic databases: MEDLINE (Ovid MEDLINE 1946 to present), EMBASE (Ovid EMBASE 1974 to present), IEEE Xplore, PsycINFO (Ovid APA PsycINFO 1806 to present), Scopus, Web of Science (All Databases) and ACM Digital Library, between May 5 and 25, 2024. This selection combined clinical and health sciences databases (MEDLINE, EMBASE and PsycINFO) with engineering and computer science databases (IEEE Xplore and ACM Digital Library) to reflect the interdisciplinary nature of BCI game research, which spans neuroscience, cognitive assessment and technology development. Scopus and Web of Science were included for their broad cross-disciplinary coverage.

Papers selection process

Papers were imported into the Covidence platform to conduct the review, where duplicates were removed. Before evaluating titles and abstracts, our team members (MA, ARR, SA, YA) were trained in applying inclusion and exclusion criteria. Two independent pairs of researchers (MA and SA; MA and YA) evaluated the titles and abstracts. Disagreements within pairs were discussed, and any unresolved issues were decided by a third rater (ARR). The same pairs reviewed the full texts of the selected papers, with any disagreements resolved by ARR, and reasons for exclusions were recorded. The level of agreement in the title, abstract and full-text screening phases was 96.3% and 91.8%, respectively.

Data extraction process

One researcher (MA) extracted the data from the final sample of the included papers and recorded it in an Excel file. Data extraction was guided by a standardized charting form developed a priori by the research team, which outlined the specific domains and variables to be extracted from each paper. Where inconsistencies or ambiguities arose during extraction, the extracting researcher flagged the item and, through discussion with at least one other team member (ARR, SA or YA), reached a resolution, with final decisions documented in the extraction file. Three researchers (ARR, SA and YA) reviewed multiple domains of the extracted data for each paper to validate the data. Papers were characterized according to their population (e.g., participants' age, sex and medical condition), research methods used (e.g., settings, study design, sample size and length of the studies), the cognitive skills assessed (e.g., attention), the technology-based assessment methods (e.g., game metrics, EEG or eye tracking), the BCI technology used (e.g., Emotiv), the experimental procedure (e.g., hardware, electrode placements and the number of channels), its signal processing parameters (e.g., frequency and signal acquisition time), the game used (e.g., name, type, description) and the standardized assessments used for comparison.

Data analysis

After data extraction was completed, the papers were categorized into three main groups according to the age groups of the participants, namely: (1) children (birth to 18 years), (2) adults (18–65 years) and (3) older adults (65+ years). Game types were categorized inductively during data extraction, based on each game's core design and primary objective as described in the included papers. Categories (including training games, action/adventure games, puzzle games, simulation games and narrative-driven games) were not defined a priori but emerged from patterns identified across the extracted data and were finalized through team discussion. Descriptive statistics were used to characterize the participants and bibliometric data of the papers in the literature review, utilizing Microsoft Excel for Mac (version 16.81). The following data fields were analyzed across all included papers: participant characteristics (age, sex and clinical status), cognitive domains assessed, BCI devices used, experimental paradigms, electrode placements, brainwave features and comparator assessments where available.

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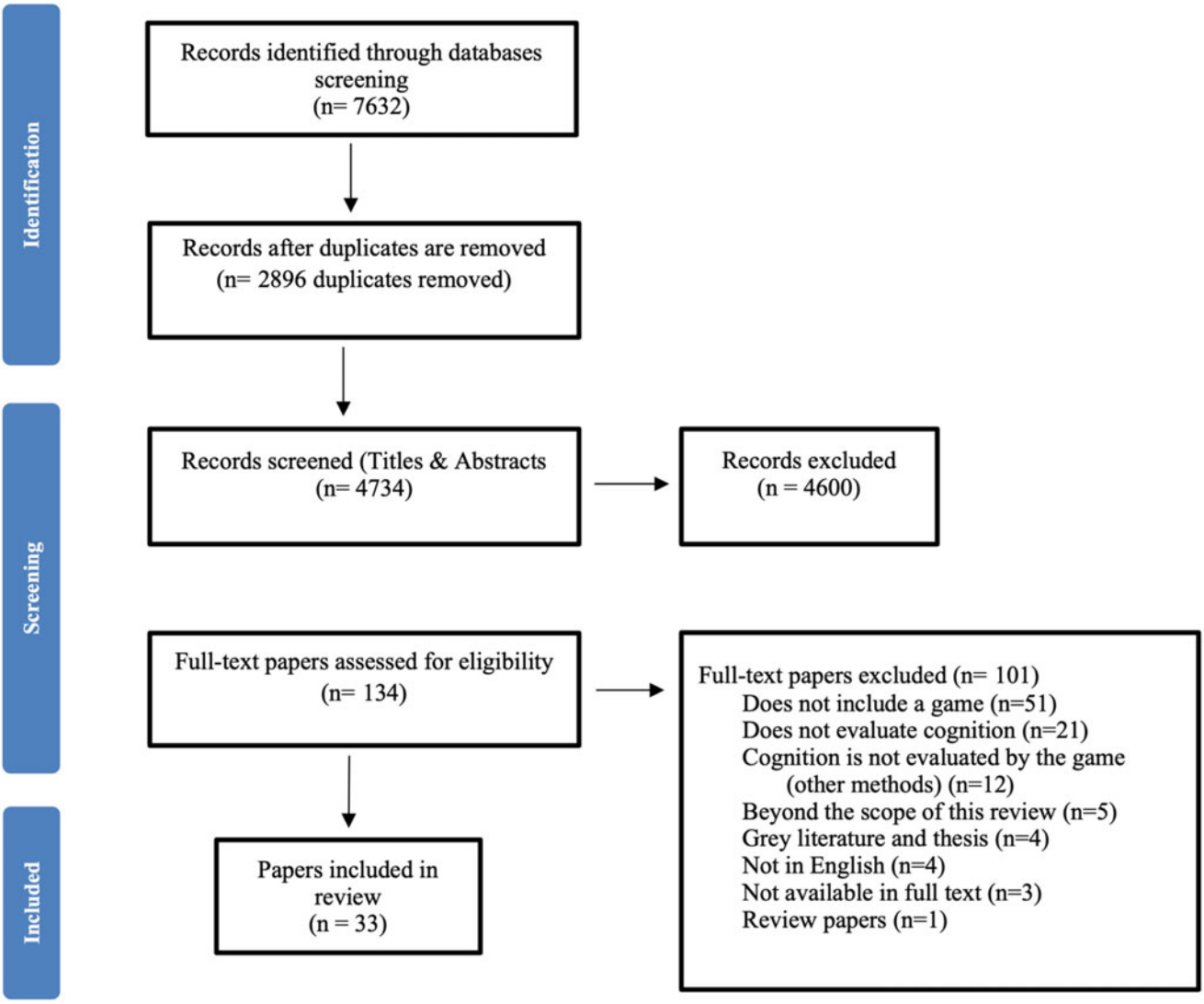


Figure 1. PRISMA flow diagram illustrating the study selection process.

Results

Papers selection

A total of 7632 papers were identified; after removing duplicates, 4734 remained for the title and abstract screening phase, 4600 were excluded during the title and abstract screening, and 101 were excluded during the full-text reading phase. Most of these studies were excluded because they did not include a game 50.5% (51/101); did not evaluate cognition 20.8% (21/101); cognition was not assessed by the game (e.g., cognition is measured by a standardized assessment and the game was used for other purposes like intervention) 11.9% (12/101); beyond the scope of the review 5% (5/101); not written in English 4% (4/101); were PhD or Masters' theses, online news outlets, magazines or one-page conference paper 3% (3/101); not available in full text 3% (3/101); or gray literature and review studies 2% (2/101). A total of 33 papers met the inclusion criteria and were, therefore, eligible for data extraction (Figure 1).

Bibliometric characteristics of the included papers

Of the 33 included papers, 54.5% (18/33) were published in academic journals, while 45.5% (15/33) were published in conference proceedings. The number of papers published per year shows a clear increasing trend, with a peak in 2019. Overall, the papers published in journals had a mean Source Normalized Impact per Paper score of 1.38 (SD = 0.56) and were primarily located in the Q1 ranking (30.3%), according to the SCImago Journal Rank classification.[31] Most papers had authors affiliated with Canada (15.2%, 5/33). Full details regarding bibliometrics are presented in Appendix B. The increasing publication trend, alongside the concentration of papers in high-impact Q1 journals, suggests that BCI game research is gaining scientific legitimacy, though the peak in 2019 and the high proportion of conference proceedings indicate that much of the work remains in early exploratory stages rather than mature clinical application.

Population characteristics

Table 1 summarizes the population characteristics. The papers included 694 participants; most papers included adults, 60.6% (20/33), while 33.4% (11/33) included children, and only 6.1% (2/33) included older adults. Only 21 out of 33 papers reported participants' biological sex. Among the 694 participants in these

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Table 1. Participant characteristics across all included studies

Age group [*n* of papers (%)]	Population				Study			
	Sample size (*n*)	Diagnosis (*n*)	Male *n* (%)	Female *n* (%)	Design (*n* of papers)	Setting (*n* of papers)	*N* of session (mean)	References
Children [11 (33.3)]	203	ADHD (116)*	91 (44.83)	24 (11.82)	Pre-post-test (5)	Clinical (4)	1–30 (7)	32,34,35,37,38,40,41,65,81,83,95
		Healthy (53)			RCT (2)			
		ASD (12)*			Cross-sectional (1)	Community (6)		
		Hearing loss (12)			Single case (1)			
		CP (10)*			Case control (1)	Both (1)		
Adults [20 (60.6)]	401	Healthy (389)	187 (46.63)	138 (34.41)	Pre-post-test (12)	Clinical (9)	1–20 (4)	22,33,34,36,38,39,54,55,66, 67,82,96–104
					RCT (4)			
		ADHD (7)			Cross-sectional (3)	Community (11)		
		DD (5)*			Longitudinal (1)			
Older adults [2 (6.1)]	37	MCI (35)*	5 (13.51)	32 (86.49)	Pre-post-test (1)	Clinical (1)	20	38,105
		Healthy (2)			RCT (1)	Community (1)		
Not specified [3 (9.1)]	53	Healthy (53)	40 (75.47)	NR*	Pre-post-test (1)	Clinical (1)	8	106–108
					RCT (1)	Community (2)		
					Cross-sectional (1)			
Total [33 (100)]	694	Healthy (497)	323 (46.5)	194 (28)	Pre-post-test (18)	Clinical (14)	1–30 (6)	
		ADHD (123)*			RCT (7)			
		MCI (35)*			Cross-sectional (5)	Community (18)		
		ASD (12)						
		Hearing loss (12)			Longitudinal (1)			
		CP (10)*			Single case (1)	Both (1)		
		DD (5)*			Case control (1)			

Notes: ADHD = attention deficit hyperactivity disorder; ASD = autistic spectrum disorders; CP = cerebral palsy; DD = development disabilities; MCI = mild cognitive impairment; NR = not reported. Some studies included more than one age group and more than one diagnosis.

studies, 28% (194/694) were female, 46.5% (323/694) were male and 25.5% (177/694) did not have their sex reported. Some studies included people with different diagnoses. Most studies included healthy participants (75.76%, 25/33), 21.2% (7/33) of the studies included individuals with attention deficit hyperactivity disorder (ADHD) and 15.15% (5/33) included other conditions like developmental disabilities (DD), autism spectrum disorder (ASD), mild cognitive impairment (MCI), CP and hearing loss. The heavy concentration of healthy adults and children with ADHD, combined with limited sex reporting and the near-absence of older adults, suggests that the field remains in a feasibility phase, with generalizability to diverse clinical populations yet to be established.

Research question 1. What BCI games are currently used for cognitive assessment, and in which populations?

The 33 included studies utilized 75 games, ranging from 1 to 14 games per study. Some of the games are commercially available, such as AVERT, Dreamskeeper, KittenQuest, CrazyFarm, Kunoichi, Brain-de-fer, Cog-Car, Pac-Man, Scalebridge, FarmerKeeper, BrainCats, REEFOCUS, FOCUS, Armis and SmartMind. Among the games used, 48% (36/75) were training, 21.3% (16/75) action/adventure, 13.3% (10/75) puzzle, 9.3% (7/75) simulation, 4% (3/75) racing, 2.7% (2/75) educational and 1.3% (1/75) narrative/story-driven.

The games were categorized based on their core design and objectives: training games focused on practicing specific cognitive skills like attention, impulse control or working memory; action/adventure games combined fast-paced challenges with exploration and problem-solving; puzzle games involved tasks like matching, sequencing or mental manipulation; simulation games replicated real-world tasks to enhance cognitive skills; racing games required participants to modulate attention to influence the speed or performance of a moving object; educational games incorporated learning objectives within game-based tasks; and narrative/story-driven games engaged players through interactive stories.

Most studies used active BCI games, where the game was actively controlled using brain signals, as opposed to those where the BCI system merely passively recorded brain activity during gameplay. The games varied in how participants interacted with them, with approximately 60% (45/75) using attention levels as the primary control command to modulate game elements such as the speed of a car, the movement of an avatar or the success of a task. Around 16% (12/75) of games used combined states (such as attention and relaxation) to influence gameplay, while approximately 12% (9/75) passively recorded EEG signals during gameplay, such as theta/beta ratios, P300 amplitudes or SMR activity, without using them to control the game directly. A smaller proportion, around 4% (3/75), employed hybrid approaches, where participants both actively controlled aspects of the game

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through EEG and had their brain activity analyzed for cognitive assessment.

Participant age groups categorized the 33 studies into children, adults and older adults. Three studies (9.1%) did not specify the age or age group of their participants. Of the 33 studies, 11 (33.3%) included children, with a total sample size of 203. The children included in those studies were diagnosed with ADHD (57.1%, 116/203), while 26.1% (53/203) had no diagnosis, 5.9% (12/203) had ASD and hearing loss each and 4.9% (10/203) had CP. Most children were male, at 44.8% (91/203), while females accounted for only 11.8% (24/203).

Most studies included adults, with 60.6% (20/33) of the total sample size of 401 individuals. The participants were predominantly with no diagnosis (97%, 389/401), with smaller proportions of ADHD (1.7%, 7/401) and developmental disorders (1.2%, 5/401). Among adults, the majority were males, comprising 46.6% (187/401), with females accounting for 34.4% (138/401).

Only two studies (6.1%) included older adults, with a total sample size of 37; most were diagnosed with MCI (94.6%, 35/37), and only two were healthy individuals (5.4%). Unlike the other age groups, most older adults were females (86.5%, 32/37), with males comprising 13.5% (5/37). The dominance of training games targeting attention, combined with the heavy reliance on active BCI control through attention modulation, suggests that game design in this field has been largely shaped by the availability of simple EEG paradigms and the characteristics of convenience samples rather than by a deliberate effort to assess a broad range of cognitive functions across diverse populations.

Research question 2. Which cognitive or perceptual skills are measured by these BCI games, and how were they measured?

Table 2 summarizes the cognitive and perceptual skills assessed. Some studies assessed only one cognitive skill, while others included multiple skills. Attention, particularly sustained attention, was the most frequently explored cognitive skill, with 87.9% (29/33) of the studies assessing it. Memory, particularly working memory, was evaluated in 27.3% (9/33) of the studies and inhibition in 18.2% (6/33), and spatial perception was measured in 12.1% (4/33). Calculation and cognitive flexibility were assessed at 6.1% (2/33) each, and language, reading comprehension, visual perception and cognitive speed were each measured at 3% (1/33).

These cognitive and perceptual skills were assessed through different methods. Only one study (3%) evaluated cognition using game performance metrics alone, such as accuracy, reaction time and error rates.[22] In contrast, brain signals (EEG) were used as the sole measure in 21.2% (7/33) of the studies.[32,33,36–38] Most studies (66.7%, 22/33) combined both approaches, integrating metrics from game performance with real-time EEG data to capture participants' ability to sustain attention, modulate arousal or engage in task-specific cognitive processes. The use of EEG allowed researchers to infer neural correlates of specific cognitive domains (such as attention, working memory or cognitive flexibility) by monitoring brainwave patterns (e.g., theta/beta ratios, P300 potentials), while game performance reflected behavioral manifestations of these cognitive skills (e.g., reaction time as a measure of attention, memory accuracy for working memory or error rates for impulse control). Additionally, one study (3%) utilized EEG and eye-tracking to measure attention and gaze patterns during gameplay.[39] Another study (3%) combined EEG, eye-tracking and game performance to assess multimodal engagement.[40] And a third study (3%) integrated EEG and motion sensors to evaluate both cognitive and motor outputs in a dynamic gaming context.[41] This multimodal approach highlights the growing interest in combining physiological and behavioral data to assess cognitive skills in a more holistic and ecologically valid manner.

The dominance of attention as the assessed cognitive domain, driven largely by its theoretical alignment with EEG paradigms and the overrepresentation of ADHD samples, indicates that BCI game research has yet to demonstrate breadth across the full spectrum of cognitive functions relevant to clinical assessment.

Research question 3. How do these BCI games for cognitive assessment compare to traditional methods?

Out of the included studies, only 9 (27.3%) used standardized cognitive assessments (not self-reported) in addition to the BCI games. There were 13 standardized assessments designed to evaluate different cognitive skills across various age groups: the Trail Making Test and Stroop Test assessed executive function and cognitive flexibility; the Tower of Hanoi measured problem-solving and planning; the Psychological Battery for Attention Assessment, Integrated Visual and Auditory Continuous Performance Test, Test of Variables of Attention (T.O.V.A.) and Conners' Continuous Performance Test (CPT/KCPT) targeted attention and inhibitory control; the Montreal Cognitive Assessment-Thai and Thai Mental State Examination evaluated global cognitive function in older adults; the Cambridge Neuropsychological Test Automated Battery (CANTAB) assessed a broad range of cognitive domains including memory and attention; the Korean Kaufman Brief Intelligence Test (K-KBIT-2) and Wechsler Intelligence Scale for Children (WISC-IV) measured general cognitive ability and intelligence in children; and the KNISE-BAAT evaluated basic academic achievement in children with disabilities.[4,42–53]

Six studies reported a correlation coefficient value ranging from moderate-to-strong correlations (r ranging between 0.52 and 0.92) between BCI game performance and standardized assessments. The strongest correlations were observed between BCI games and attention-focused tools such as T.O.V.A. and CPT, suggesting that BCI games are most valid for assessing attentional constructs, which aligns with the predominance of attention paradigms in the reviewed studies. Moderate correlations with broader cognitive batteries such as CANTAB and WISC-IV indicate that BCI games show preliminary convergent validity across a wider range of domains, though these findings require replication in larger, more diverse samples before clinical validity can be established. In those studies, BCI systems were often perceived as more engaging and adaptable compared to standardized tests. Games in some studies demonstrated high classification accuracies (i.e., 69.2%, 75%, 91.6%, 98.77%) in distinguishing attention states (identifying whether a person is in an attentive or inattentive mental state) comparable to or exceeding those of standardized tools.[82] The limited use of standardized comparators across studies means that, while moderate-to-strong correlations are promising, they are insufficient to establish clinical validity at this stage, underscoring the need for more systematic psychometric benchmarking in future research.

Research question 4. What BCI technologies are used to assess cognition, what electrode placement is used and what brain waves are explored?

Fourteen different BCI technologies were used, as summarized in Table 3. MindWave was used the most at 42.4% (14/33), Emotiv EPOC+ was used at 21.2% (7/33) and Cognionics was used in 6.1% of the studies (2/33). The following technologies were used in one study, each with a percentage of 3%: g.USBamp, BrainProducts, B-

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Table 2. Cognitive and perceptual skills assessed across the included studies

Cognitive skills [*n* of papers (%)]	Game type (*n* of papers)	Electrode placement region (*n* of papers)	Brainwave (*n* of papers)	Reference
Attention [29 (87.9)]	Training (8)	Frontal and prefrontal (26)	Beta (27)	22,33–41,54,55,65,66,81–83,95,96,98–100,102–108
	Action/adventure (7)		Alpha (21)	
	Puzzle (7)	Central (7)	Theta (20)	
	Simulation (4)	Parietal (6)	Delta (10)	
	Racing (3)	Temporal (4)	Gamma (10)	
	Educational (2)	Occipital (3)		
	Narrative/story-driven (1)			
Memory [9 (27.3)]	Action/adventure (3)	Frontal and prefrontal (4)	Beta (9)	32,66,81,95,97,99,101,103,105
	Simulation (1)	Central (3)	Theta (9)	
	Racing (1)	Parietal (3)	Alpha (8)	
	Puzzle (1)	Temporal (3)	Delta (3)	
	Training (1)	Occipital (2)	Gamma (3)	
Inhibition [6 (18.2)]	Action/adventure (3)	Frontal and prefrontal (8)	Beta (5)	32,41,66,81,95,101
	Puzzle (2)	Central (3)	Theta (5)	
	Training (2)	Parietal (3)	Alpha (4)	
	Racing (1)	Temporal (3)	Delta (1)	
	Narrative/story-driven (1)	Occipital (3)		
	Simulation (1)			
Spatial perception [4 (12.1)]	Action/adventure (3)	Frontal and prefrontal (4)	Alpha (3)	66,67,101,107
	Racing (1)	Central (3)	Theta (3)	
	Simulation (1)	Parietal (3)	Beta (2)	
	Training (1)	Temporal (2)		
	Puzzle (1)	Occipital (2)		
Calculation [2 (6.1)]	Action/adventure (1)	Prefrontal (1)	Theta (5)	65,107
	Educational (1)	Parietal (1)	Beta (2)	
			Alpha (1)	
Cognitive flexibility [2 (6.1)]	Action/adventure (2)	Frontal and prefrontal (2)	Alpha (2)	32,101
	Puzzle (1)	Central (2)	Theta (2)	
	Simulation (1)	Parietal (2)	Beta (1)	
		Temporal (2)		
		Occipital (2)		
Language [1 (3)]	Action/adventure	Frontal and prefrontal	Alpha	66
	Puzzle	Central	Beta	
	Simulation	Parietal		
		Temporal		
		Occipital		
Reading comprehension [1 (3)]	Narrative/story-driven	Prefrontal	Beta	41
			Theta	
Visual perception [1 (3)]	Training	Frontal	NR *	55
		Central		
		Parietal		
		Occipital		
Cognitive speed [1 (3)]	Training	Frontal	NR *	55
		Central		
		Parietal		
		Occipital		

Notes: NR = not reported. Some of the studies assessed more than one cognitive skill.

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Table 3. Brain–computer interface technologies reported across the included studies

Technology used [*n* of papers (%)]	Most used electrode placement (*n* of papers)	Number of channels range (mean)	Frequency of signal acquisition used (in Hz)	References
MindWave [14 (42.4)]	Fpz (12)	1	NR/256/512	34,38,40,41,54,65,66,83,95, 96,99,102,105,106
	Fp1 (2)		256/512	
Emotiv EPOC+ [7 (21.2)]	P8 (2)	1–14 (10)	128	32,36,100,103,104,107,108
	AF3, F7, F3, F4, F8, O1,02, P7 (3)			
g.tec Unicorn Hybrid [1 (3)]	Fp1, Fp2, PO7, PO8 (2)	14–17 (16)	250	39
g.USBamp [1 (3)]	Oz, Fpz, Fz	3	512	22
BrainProducts [1 (3)]	NR	64	500	67
B-Alert X24 [1 (3)]	Fz, F1, F2, F3, F4, Cz, C1, C2, C3, C4, CPz, Pz, P1, P2, POz	24	256	33
OpenBCI [1 (3)]	F7, FP1, FP2, F8, F3, F4, C3, Cz, C4, P7, P3, Pz, P4, P8, O1, O2	16	256	97
Procomp2 [1 (3)]	Cz, FCz	2	128	81
BrainMaster 2EBII [1 (3)]	FP1, FP2, F3, Fz, F4, F7, F8, T3, C3, Cz, C4, T4, T5, T6, P3, Pz, P4, O1, O2	19	256	101
Enobio [1 (3)]	F3, F4, Fz, C3, C4, Cz, Fp1, Fp2	8	500	37
Muse S [1 (3)]	AF7, AF8, TP9, TP10	4	256	106
NirSmart [1 (3)]	R-PFC, L-PFC, R-MC, L-MC	40	10	96
Cognionics [2 (6.1)]	F3, F7 (2)	20	500	82,98
MyndPlay [1 (3)]	Fpz	1	512	35
Not reported [1 (3)]	Fz, Cz, Pz, P3, P4, P7, P8, Oz	8	500	55

Notes: NR = not reported. Some of the studies assessed more than one cognitive skill.

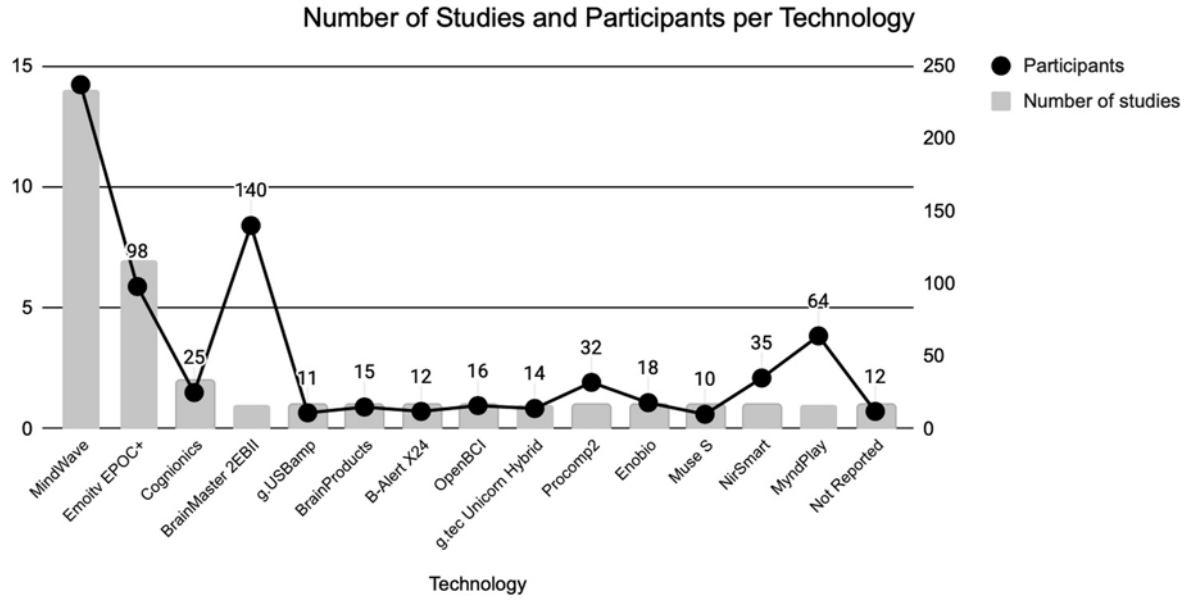


Figure 2. Number of studies and participants per brain–computer interface technology used.

Alert X24, OpenBCI, Procomp2, g.tec Unicorn Hybrid, BrainMaster 2EBII, Enobio, Muse S, NirSmart and MyndPlay. One study (3%) did not report the specific technology used (Figure 2).

Although not all studies explicitly stated the specific BCI paradigm they employed, some described the underlying paradigm. For example, one study employed the P300 paradigm by using a three-level oddball-based game controlled via EEG, where target stimuli evoked P300 signals that were classified using the t-RIDE algorithm to adapt the game difficulty in real time.[55] Another study employed the steady-state visual evoked potential paradigm, where participants focused on flickering visual stimuli at

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different frequencies (7 and 9 Hz) to control actions in a 3D virtual classroom game.[22] A third study used the motor imagery paradigm, training participants to engage in distinct mental tasks such as imagining movement or performing mental arithmetic, which were then detected through EEG signals to guide navigation in a maze game.[33] The 10–20 system dominated as the standard framework, with electrodes commonly placed in the frontal, central, parietal and occipital regions, depending on the study's focus. The most frequent sites were Fpz (forehead) for ground/reference, Fz for frontal activity and Cz/Pz for central and parietal monitoring. The number of channels varied from 1 to 64 in those studies. EEG findings were largely consistent with the cognitive constructs assessed. Beta (β) and theta (θ) waves, closely associated with attention modulation and working memory, were the most frequently reported, appearing in 87.9% (29/33) and 69.7% (23/33) of the studies, respectively, reflecting the predominance of attention-focused paradigms.[56,57] Alpha (α) waves, linked to cognitive inhibition and relaxation states, were reported in 72.7% (24/33) of the studies.[58,59] Delta (δ) and gamma (γ) activity, associated with higher-order cognitive processing and problem-solving, were the least reported, each appearing in 33.3% (11/33) of the studies, suggesting that more complex cognitive constructs remain underexplored in current BCI game research.[60,61]

The predominance of consumer-grade single or low-channel devices such as MindWave and Emotiv, alongside the variability in electrode placements and brainwave features reported, reflects a field still negotiating the balance between accessibility and scientific rigor. Table 4 summarizes the included studies.

Discussion

BCI games that are currently used for cognitive assessment and in which populations

Most studies in this review focused on healthy male adults, highlighting an underrepresentation in participant characteristics across age, sex and clinical status. The average age across studies is around 26.5 years, with pediatric samples being limited and fragmented, ranging from 3.5 to 16 years old. In terms of sex distribution, a marked imbalance was evident; most studies skewed heavily toward male participants, with some samples being 100% male. Most participants were healthy individuals (76%), with smaller subsets including individuals with ADHD (18%) and other conditions. Notably, the overrepresentation of ADHD in pediatric samples (57% of children participants) further narrowed the scope of BCI research, reinforcing a focus on attention-related assessments, a pattern likely driven by convenience sampling and the natural fit of attention tasks with EEG paradigms. While neurotypical adults offer a convenient starting point for assessing BCI game usability and performance, they do not represent the full spectrum of potential end-users, especially those who benefit most from nonverbal, adaptive cognitive assessments. This limits the external validity and real-world applicability of BCI game findings, underscoring the need for more diverse recruitment strategies and standardized sex-disaggregated reporting in future studies.[62–64]

The types of games used across studies varied, but a clear pattern emerged. Nearly half of the games were training games designed to target attention or working memory through repetitive tasks, neurofeedback and adaptive difficulty (e.g., FOCUS, REEFOCUS).[35,36] Action/adventure games incorporated fast-paced challenges or exploratory tasks (e.g., FarmerKeeper, BrainCats).[40] Puzzle games involved logic, memory matching or spatial manipulation (e.g., Scalebridge, text rotation games).[65,66] Less frequently, studies used simulation games (e.g., AVERT) to recreate real-world tasks or narrative-driven games (e.g., fairy-tale games) to engage users in story-based interactions.[67] Most games relied on attention as the primary control command, with players modulating game elements such as speed, movement or task success based on EEG signals. A smaller proportion of studies combined EEG with other modalities, such as motion sensors or eye-tracking, to create more immersive, multimodal gaming experiences.

Cognitive and perceptual skills measured by BCI games, and how were they measured

The adaptability of BCI games stands out as a major strength, offering a flexible, user-centered approach to cognitive assessment. This is particularly relevant for populations with motor or communication challenges, where traditional methods often fall short. However, the narrow focus on specific cognitive domains, predominantly attention, limits the broader applicability of current findings. The overreliance on attention as the primary cognitive skill assessed in BCI games is a critical finding of this review. This narrow focus is directly tied to the participant demographics, particularly the overrepresentation of children with ADHD in pediatric samples. The suitability of EEG-based paradigms (e.g., theta/beta ratio) for detecting attentional variations makes this a theoretically grounded starting point for BCI research; however, it has inadvertently limited the scope of the field.[68,69] Other cognitive domains are equally tractable via EEG: working memory can be indexed by theta oscillations and P300 amplitude, cognitive flexibility by frontal alpha asymmetry and error-related negativity and problem-solving by gamma-band synchronization.[58,70–72] BCI games targeting these domains could be validated against established neuropsychological tools, providing a principled psychometric bridge between neural signals and clinically recognized constructs. A more deliberate effort to expand beyond attention is needed to demonstrate the full potential of BCI games as comprehensive cognitive assessment tools. Future research should prioritize designing and validating BCI games for a broader range of cognitive domains, such as memory, problem-solving and executive function, to broaden the clinical applicability of this technology across diverse populations. In the few studies involving older adults, the focus shifted slightly toward attention and memory, reflecting the relevance of these domains for age-related cognitive decline and conditions like MCI.[73]

Moreover, only a few studies have assessed skills such as memory, problem-solving or cognitive flexibility, highlighting a need for more comprehensive assessment frameworks. These findings align with previous studies, emphasizing the promise of task-specific BCIs for cognitive enhancement while noting protocol standardization and user adaptation challenges.[74] Similarly, other studies highlighted the role of gamification in improving engagement and stressed the importance of robust validation against standardized assessments – a recurring theme in this review.[14,75–77]

The methods used to measure these cognitive skills varied as well. Most studies combined game performance metrics (e.g., accuracy, reaction time, errors) with EEG signals, allowing researchers to infer neural correlates of cognitive states while also capturing behavioral outcomes. This combined approach enhances the ecological validity of assessments, as it links brain activity with task performance in real time.[78,79] However, a small number of studies relied solely on EEG data or game performance, which

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Table 4. Summary of included studies

Author, year	Age group (diagnosis)	*n*	Cognitive domain(s)	BCI device	Game name (type)	Key findings
Chen et al., 2024	Adults (healthy)	35	Attention	MindWave NirSmart (fNIRS)	Car racing games (racing)	The study found that physical games led to stronger brain activation and higher intrinsic motivation compared to video games.
Ali & Puthusserypady, 2015	Adults (healthy)	11	Attention	g.USBamp	3D classroom game (educational)	The SSVEP-BCI system achieved a high mean accuracy (92.26%) and an average selection time of about 3 s, showing it can measure and train attention.
Kenny et al., 2019	Adults (healthy)	15	Spatial perception	BrainProducts	AVERT (simulation)	Improved navigation performance: participants' time to navigate tasks improved significantly during the initial training blocks and then stabilized, indicating proficiency.
Mondéjar et al., 2016	Children (healthy)	12	Inhibition memory cognitive flexibility	Emotiv EPOC+	Dreamskeeper – KittenQuest (action/adventure) CrazyFarm – Kunoichi (puzzle)	Certain video game mechanics (timely action, learning patterns and logical puzzles) significantly activated the brain's prefrontal area, linked to executive functions.
Myrden & Chau, 2015	Adults (healthy)	12	Attention	B-Alert X24	Maze navigation game (puzzle)	Participants' BCI performance improved over time, with accuracy nearing 70% by the third session.
Delisle-Rodriguez et al., 2023	Adults (healthy)	20	Attention	Cognionics	Neurofeedback Space (simulation)	The BCI achieved up to 98% accuracy in classifying attention and non-attention states using SVM-RBF.
Georgitsaros et al., 2023	NS (healthy)	10	Attention	MindWave Muse S	Brain-de-fer (action/adventure)	The model produces more spikes than the smoother value of MindWave.
Chen & Sui, 2023	Adults (healthy)	16	Memory	OpenBCI	Game 1 (Moon Rise Game) – Game 2 (Spacecraft Game) (simulation)	Neurofeedback training significantly increased alpha-band activity in the prefrontal and occipital regions.
Machado et al., 2022	Adults (healthy)	5	Attention	Cognionics	Neurofeedback Space (simulation)	Most participants showed improvement in their attention levels, as reflected in the game metrics and the standardized Concentrated Attention Test.
Kandemir & Kose, 2022	Children/adults (healthy/deaf)	28	Attention	MindWave	Fruit Picking – Air Hockey (action/adventure) Maze (puzzle)	The games significantly boosted attention levels in over 70% of adult participants, as measured by an EEG device.
Kosmyna et al., 2021	Adults (healthy)	14	Attention	g.tec Unicorn Hybrid	Unnamed game (simulation)	The attention-aware system significantly improved usability and reduced distractions compared to an attention-unaware system.
Kong & Song, 2021	Adults (DD)	5	Attention memory inhibition cognitive flexibility spatial perception	MindWave	Mental racing (racing), mole catching (action/adventure), card flipping – text rotation (puzzle)	Neurofeedback games significantly improved cognitive functions in adults with developmental disabilities.
Israsena et al., 2021	Older adults (healthy/MCI)	35	Attention memory	MindWave	Run run – Sunshine day – Cast away – Paper plane – 321 Shoot (action/adventure)	Significant cognitive improvements in visual memory, attention and visual recognition memory after the intervention.
Khan et al., 2020	Adults (healthy)	10	Attention memory	MindWave	Puzzle game (puzzle)	Cognitive performance improved significantly, with attention increasing from 74% to 98% over trials.
Moghaddas et al., 2020	Adults (healthy)	10	Attention	Emotiv EPOC+	Cog-Car (racing)	Participants' focus and attention improved significantly over three consecutive days of testing.

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Table 4. Summary of included studies (*Continued*)

Author, year	Age group (diagnosis)	*n*	Cognitive domain(s)	BCI device	Game name (type)	Key findings
Rajabi et al., 2019	Children (ADHD)	32	Attention inhibition memory	ProComp2	SmartMind (training)	Combining neurofeedback with game-based cognitive training significantly improved ADHD symptoms, particularly in attention and impulsivity.
Gordon et al., 2020	Adults (healthy)	140	Memory inhibition spatial perception	BrainMaster 2EBII	Pac-Man (action/adventure) Ball filling (simulation)	The neurofeedback training led to significant improvements in increasing upper alpha brainwave activity during sessions, with both within-session and across-session learning observed.
Tahai et al., 2019	Children (healthy)	20	Attention calculation	MindWave	Scalebridge (educational)	The adaptive group completed the game with fewer trials, indicating faster acquisition of proportional reasoning.
Mercado et al., 2019	Children (ASD)	12	Attention	MindWave	FarmerKeeper – BrainCats (training)	FarmerKeeper outperformed BrainCats in terms of sustaining participants' attention.
Park et al., 2019	Children (ADHD)	5	Reading comprehension attention behavioral inhibition	MindWave	Adaptive Behaviour Training Game Platform (narrative/story)	Improved reading skills, with significant gains in reading aloud and comprehension.
Georgiou et al., 2019	Children (ADHD)	64	Attention	MyndPlay	REEFOCUS (training)	Attention levels showed slight but statistically significant improvement, especially in the Multisensory Mixed Reality mode.
Ochi et al., 2017	Adults (healthy/ADHD)	17	Attention	MindWave	Armis (action/adventure)	The ADHD-risk group showed significant improvements in sustained attention and accuracy on the T.O.V.A.
Vasiljevic et al., 2018	Adults (healthy)	24	Attention	MindWave	Mental War (action/adventure)	Participants generally found the Mental War game engaging and enjoyable.
Alchalabi et al., 2017	Adults (healthy)	5	Attention	Emotiv EPOC+	FOCUS (training)	The study achieved up to 96% accuracy in classifying attention using EEG signals collected during gameplay.
Perales & Amengual, 2016	Children (healthy/CP)	18	Attention	Enobio	Serious video game labyrinth (puzzle)	Children with CP exhibited lower alpha, theta and beta power band values than controls, with an abnormally higher theta/beta ratio, similar to ADHD patterns.
De Venuto et al., 2016	Adults (healthy)	12	Cognitive speed attention visual perception	NR	P300-based cognitive game/test (training)	P300 amplitude decreased, and latency increased as task difficulty increased, indicating higher cognitive demands.
Liu et al., 2015	NR (healthy)	40	Spatial perception attention calculation	Emotiv EPOC+	Shooting game (action/adventure)	Fractal dimension-based neurofeedback was as effective as the traditional theta/beta ratio-based neurofeedback in improving cognitive performance across several tasks.
Jiang & Johnstone, 2015	Children (ADHD)	5	Attention inhibition memory	MindWave	Working memory, impulse control and state control games (×14) (training)	The neurocognitive training showed improvement in attention, impulse control and relaxation, which are cognitive functions commonly associated with ADHD
Navalyal & Gavas, 2014	Children/adults/older adults (healthy)	21	Attention	MindWave	BCI game (simulation)	Attention levels improved with mental training, especially among Abacus students.
Thomas et al., 2014	NR (healthy)	3	Attention	Emotiv EPOC+	Neurofeedback game (puzzle)	Attention-shift detection using alpha-band energy showed an average accuracy of 72.22%
Thomas & Vinod, 2016	Adults (healthy)	24	Attention memory	Emotiv EPOC+	Attention-driven neurofeedback game (puzzle)	The study found that neurofeedback significantly improves attention and cognitive skills.

(*Continued*)

Table 4. Summary of included studies (*Continued*)

Author, year	Age group (diagnosis)	*n*	Cognitive domain(s)	BCI device	Game name (type)	Key findings
Chen et al., 2017	Children (ADHD)	10	Attention	MindWave	Vigilance, sustained, divided and selective attention (training)	The SNAP-IV scores showed a notable decrease in both attention deficit and hyperactivity symptoms after the training sessions, with highly significant p-values.
Alchalabi et al., 2018	Adults (ADHD)	4	Attention	Emotiv EPOC+	FOCUS (training)	98% accuracy in distinguishing ADHD from non-ADHD participants using EEG signals.

Note: *n* = sample size; ADHD = attention deficit hyperactivity disorder; ASD = autism spectrum disorder; CP = cerebral palsy; DD = developmental disabilities; EEG = electroencephalogram; MCI = mild cognitive impairment; NR = not reported; SSVEP-BCI = steady-state visual evoked potential-brain–computer interface; T.O.V.A. = test of variables of attention; SVM-RBF = Support Vector Machines with a Radial Basis Function.

may limit the depth and reliability of cognitive insights, particularly in complex domains such as memory or problem-solving. A few studies incorporated additional sensors, such as eye-tracking and motion sensing technologies, to create multimodal BCI systems. These setups aimed to capture a more holistic profile of user engagement, combining neural, behavioral and physical data streams. While promising, these multimodal approaches also introduce technical challenges, including comfort issues with wearing multiple devices, data synchronization problems and potential signal interference between sensor systems.[80]

BCI games for cognitive assessment compared to traditional methods

Compared to traditional cognitive assessments, BCI games are emerging as promising alternatives that combine neurophysiological monitoring with interactive, user-centered design. Most studies reviewed demonstrated moderate-to-strong correlations between BCI game performance and standardized cognitive assessments, supporting their validity for evaluating cognitive functions. These findings suggest that BCI games hold promise as engaging tools for cognitive training, particularly in attention-related tasks, and may offer enhanced engagement compared to traditional assessments. Several studies report that BCI games increase participant motivation, enjoyment and sustained involvement, especially in children with ADHD, suggesting a potential advantage in user engagement.[35,41,81–83] Real-time feedback, gamified environments and the ability to tailor difficulty levels can enhance user engagement, contribute to higher classification accuracies and improve the quality of EEG signals by reducing movement artifacts caused by boredom, fatigue or inattention. When users are motivated and engaged, they are more likely to maintain focus and minimize erratic movements, resulting in cleaner and more stable EEG patterns that enhance the reliability of classification. These features align with previous research that emphasizes the role of gamification in improving motivation and data quality in cognitive assessments.[19] For example, in a recent study, participants played a gamified "stunt plane" task with adaptive difficulty, and optimal engagement (measured via EEG indices like $\beta/(\theta + \alpha)$) correlated with high classification accuracy (within-subject F1 $\approx$ 0.89, cross-subject F1 $\approx$ 0.81), indicating that sustained engagement yields cleaner, more classifiable EEG patterns.[84] These findings point to adaptive difficulty as a particularly valuable design feature, one that simultaneously sustains user motivation and stabilizes EEG signal quality, making it a practical target for future BCI game development protocols.

BCI technologies used to assess cognition, the electrode placement used and the brain waves explored

The review revealed considerable variability in the BCI technologies and setups used to assess cognition. While the 10–20 system was the standard for electrode placement, the number of channels varied widely, ranging from single-channel consumer-grade devices to high-density 64-channel systems, reflecting a tension between accessibility and signal quality. Lower-cost, widely used devices like the MindWave and Emotiv EPOC+, the most frequently reported technologies in this review, offer ease of use and portability but are limited by factors such as fewer channels, fixed electrode positions and lower signal fidelity.[85,86] Reduced electrode counts and fixed placements can affect both sensitivity and specificity. With fewer electrodes, the system has reduced spatial coverage, which limits its ability to detect subtle or localized

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neural signals associated with specific cognitive processes, thereby reducing sensitivity. Cognitive assessment research confirms that higher channel counts yield better sensitivity.[87] Specificity is also affected, as narrow spatial coverage and the inability to place electrodes optimally make it difficult to distinguish between true cognitive events and non-target or artifact activity. Previous research has demonstrated that reducing channel count is associated with increased false positive rates, suggesting that consumer-grade devices, ranging from a single channel (MindWave) to 14 channels (Emotiv EPOC+), may compromise the accuracy and reliability of cognitive signal detection despite their accessibility and ease of use.[87,88] Research-grade systems like BrainProducts ActiChamp, with 32–64 or more channels, provide higher resolution and more precise data and yet remain less feasible for scalable or real-world applications due to cost and complexity. Future studies should directly compare consumer-grade and research-grade systems within the same paradigm to quantify the trade-off between accessibility and signal fidelity and to establish the minimum channel count required for reliable cognitive assessment.

The choice of technology influences both the cognitive domains assessed and the brain signals captured. For instance, many studies using MindWave and Emotiv relied on predefined metrics like "attention" and "meditation" scores based on proprietary algorithms, which can obscure the interpretability and reproducibility of results. These devices tend to focus on frontal or central sites (e.g., Fz, Cz, Pz), aligning with their emphasis on attention and executive functions. Beta (β) waves were the most frequently analyzed, followed by alpha (α) and theta (θ), reflecting their established relevance in cognitive tasks such as attention modulation, working memory and task engagement.[56–58] In contrast, delta (δ) and gamma (γ) activity were reported in only one-third of the studies, suggesting that cognitive processes linked to deep learning states or higher-order integrative functions may be underrepresented in current BCI game research.[61,89]

Beyond device selection, the field would benefit considerably from standardized reporting practices across all stages of EEG data collection and analysis. The studies included in this review varied widely in how they reported electrode placement, sampling rates, preprocessing steps and analytic pipelines, making cross-study comparison difficult and limiting reproducibility. Inconsistent reporting of preprocessing decisions, such as filtering parameters, artifact rejection methods and reference schemes, has been shown to systematically alter signal quality and lead to notably different conclusions even when the same paradigm is used.[90] Adopting transparent and consistent reporting standards, including full documentation of electrode configurations, sampling rates, artifact-handling procedures and feature-extraction methods, is essential for building a cumulative and reproducible evidence base in BCI game research. Frameworks and open-source pipelines, such as Pipeline for EEG Processing and EEGLAB-based toolchains, have been proposed to support this standardization effort and should be considered reference points for future BCI game studies.[91,92]

As BCIs are increasingly considered for use with vulnerable populations, ethical and accessibility considerations must be addressed. Neural data collected through EEG can reveal sensitive information about cognitive and emotional states, raising concerns around data privacy and informed consent, particularly when participants are children or individuals with cognitive, speech and/or motor impairments.[93] Physical comfort and wearability of EEG devices also present practical challenges for these groups, as device fit and setup time can affect both participant tolerance and data quality.[17] Future studies should adopt user-centered design principles and clear data governance protocols to ensure BCI games are both ethically sound and genuinely accessible.

Limitations

This scoping review has limitations that should be acknowledged. First, the review included only English-language publications, which may have introduced language bias and excluded potentially relevant studies published in other languages.[94] Furthermore, the exclusion of documents, such as theses and book chapters, may have led to an underrepresentation of emerging research in this field. Second, a device-related bias should be noted: several studies relied on proprietary metrics such as the "attention" and "meditation" scores generated by consumer-grade devices like MindWave and Emotiv EPOC+. Because these metrics are derived from undisclosed algorithms, they limit cross-study comparability and make it difficult to draw consistent conclusions about the cognitive constructs being assessed. Third, as is consistent with scoping review methodology, no formal quality appraisal of included studies was conducted; while this is appropriate given the review's aim to map the breadth of available evidence, it means that study quality was not systematically weighted, and publication bias, whereby studies with positive or significant findings are more likely to be published, cannot be ruled out.

Future direction

Future research should address several critical priorities. First, BCI game-based cognitive assessments must be expanded to include diverse and underrepresented populations, particularly children with DD beyond ADHD, older adults with conditions like dementia and individuals with motor or communication impairments who could benefit most from non-verbal assessment tools. Second, the range of cognitive domains assessed should extend beyond attention to include memory, problem-solving, executive function and cognitive flexibility, through the development and validation of task-specific games. Third, future studies should rigorously validate BCI-based assessments against gold-standard neuropsychological measures using robust psychometric frameworks to establish reliability, validity and sensitivity to cognitive change. Fourth, transparent and consistent reporting of EEG configurations, preprocessing steps and analytic pipelines is essential to improve reproducibility and cross-study comparability. Finally, larger, longitudinal and ecologically valid studies are needed to assess the feasibility of integrating BCI games into clinical and educational workflows, examining outcomes such as user engagement, cognitive development trajectories and real-world diagnostic utility.

Conclusion

This scoping review demonstrates that BCI games are a promising and engaging medium for cognitive assessment, offering real-time neural insights without the motor or verbal demands of traditional tools. However, the field remains narrow in scope: research has disproportionately focused on attention in healthy adults and children with ADHD, while broader cognitive constructs, such as memory and clinically relevant populations, including individuals with motor impairments or age-related cognitive decline, remain underexplored. Equally pressing is the limited validation against

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standardized neuropsychological measures, which constrains clinical credibility and generalizability. Moving forward, the field must prioritize inclusive study designs, transparent reporting of BCI configurations and rigorous psychometric benchmarking to establish BCI games as reliable assessment instruments. With these advances, BCI-based games hold genuine potential to become accessible, motor-free tools for cognitive assessment that serve diverse populations across the lifespan.

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